6G6Z0048 Artificial Intelligence: 1CWK100

# 1) Longlisting

### Supervised Learning

1. **k-Nearest Neighbours (k-NN):**
   * **Brief Explanation:** k-Nearest Neighbours is a simple, yet effective, supervised learning algorithm used for classification and regression. In k-NN, the input consists of the k closest training examples in the feature space. The output is a class membership for classification tasks: an object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbour.
   * **Link to Image Classification:** In image classification, k-NN is used to classify images based on the closest feature space representation in the training set. It considers the 'k' most similar images from the training data (where similarity is usually defined in terms of distance metrics like Euclidean distance) and makes predictions based on the majority label of these neighbours. k-NN is particularly beneficial when the data is well-segmented into distinct classes, and the similarity measure effectively represents the closeness of the images.
2. **Convolutional Neural Networks (CNNs) with Transfer Learning:**
   * **Brief Explanation:** Convolutional Neural Networks (CNNs) are a specialized kind of neural network for processing data that has a known grid-like topology, especially good for image data. They use convolutional layers to filter inputs for useful information. Transfer learning involves taking a pre-trained CNN (usually trained on a large dataset like ImageNet) and repurposing it for a new, related task. This approach allows leveraging learned features without starting from scratch.
   * **Link to Image Classification:** CNNs are particularly powerful in image recognition and classification tasks because they can detect hierarchical patterns in images (like edges, textures, and shapes). With transfer learning, you can use these pre-learned patterns to boost performance on your specific image classification problem, even with a smaller dataset. This method is particularly beneficial for startups and smaller companies that might not have the vast amounts of data or resources needed to train large models from scratch.
3. **Integrated Feature Extraction:**
   * **Brief Explanation:** Integrated feature extraction refers to using a combination of techniques to transform raw image data into a reduced set of meaningful features for classification. This approach combines edge detection to identify boundaries and shapes, colour removal to simplify the data and focus on texture and structure, hand-crafted features to incorporate specific domain knowledge and highlight particular characteristics of the images, and Bag of Visual Words to create a 'vocabulary' of visual features.
   * **Link to Image Classification:**
     + **Edge Detection**: Provides a structural understanding of images by highlighting object boundaries, essential for recognizing and distinguishing objects in various conditions.
     + **Colour Removal**: Reduces computational complexity and allows algorithms to focus on structural and textural information by eliminating colour variability.
     + **Hand-Crafted Features**: Encompasses a variety of techniques like texture descriptors, shape descriptors, and more, tailored to capture essential information specific to the image classification task at hand.
     + **Bag of Visual Words (BoVW)**: A model for feature extraction in image data that treats images as if they were documents and features as if they were words. It involves extracting key features from images, quantizing these features into a set of predefined "visual words" by clustering, and then representing images as histograms of these words. This method is effective for capturing the occurrence and distribution of visual features in an image, allowing for classification based on this distribution.
4. **Support Vector Machines (SVMs):**
   * **Brief Explanation:** SVMs are a set of supervised learning methods used for classification, regression, and outliers detection. They are effective in high-dimensional spaces and particularly suited for situations where the number of dimensions exceeds the number of samples. SVMs are known for their robustness and effectiveness in capturing complex relationships in data.
   * **Link to Image Classification:** In image classification, SVMs can be used to classify images by separating image features with a hyperplane. They are especially powerful when combined with kernel functions, allowing them to handle non-linear relationships and perform well even with complex image data.
5. **Random Forests:**
   * **Brief Explanation:** Random Forest is an ensemble learning method for classification, regression, and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. They are known for their ability to reduce overfitting.
   * **Link to Image Classification:** For image classification, Random Forests can be used to handle various features extracted from images and make decisions based on the consensus of multiple decision trees. This approach is beneficial for handling diverse and complex data sets with multiple features, common in image classification.
6. **Artificial Neural Networks (ANNs):**
   * **Brief Explanation:** ANNs are computing systems vaguely inspired by the biological neural networks that constitute animal brains. They learn to perform tasks by considering examples, generally without being programmed with task-specific rules. They are known for their flexibility and capacity to learn complex patterns.
   * **Link to Image Classification:** While not as specialized for image data as CNNs, ANNs can still be employed in image classification to learn the mapping of image inputs to outputs. They are particularly useful when the classification problem involves understanding complex relationships between image features.

### Unsupervised Learning

1. **K-Means Clustering:**
   * **Brief Explanation:** K-means is a popular unsupervised learning algorithm used for clustering. It partitions the data into K distinct clusters based on feature similarity, often using distance metrics.
   * **Link to Image Classification:** In image classification, K-means can be used to segment images into clusters based on pixel similarity or feature representation. This can be particularly useful for image segmentation, object recognition, or as a preprocessing step to reduce dimensionality and identify salient features in images without labelled data.
2. **Autoencoders:**
   * **Brief Explanation:** Autoencoders are a type of neural network used to learn efficient coding of unlabelled data. The network is trained to compress the input into a lower-dimensional code and then reconstruct the input from this encoding.
   * **Link to Image Classification:** Though not directly a classification tool, autoencoders can be used in image classification to learn a compressed representation of images, which can then be used for feature extraction or dimensionality reduction before applying another classification technique. This is particularly useful when you have a large amount of unlabelled image data.
3. **Principal Component Analysis (PCA):**
   * **Brief Explanation:** PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. The transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component, in turn, has the highest variance possible under the constraint that it is orthogonal to the preceding components.
   * **Link to Image Classification:** In the context of image classification, PCA can be used for feature extraction and dimensionality reduction. High-dimensional image data can lead to complex models that are overfit, slow to train, and difficult to understand. By reducing the dimensionality, PCA helps in mitigating these issues, speeding up computation, and potentially improving model performance by reducing noise and focusing on the most informative features. It's particularly useful in preprocessing stages for both supervised and unsupervised learning models to make them more efficient and effective.

### Semi-supervised Learning

1. **K-Means Clustering with labelled images:**
   * **Brief Explanation:** In a semi-supervised context, K-means clustering can be used to organize unlabelled data into clusters based on their feature similarities. Once clusters are formed, the labelled data can be used to assign labels to each cluster, effectively spreading the label information from a small set of labelled examples to a larger set of unlabelled data. Alternatively, labelled data can guide the clustering process itself, influencing the formation of clusters to align with known categories.
   * **Link to Image Classification:** This technique is particularly useful in image classification scenarios where you have some labelled images but a large amount of unlabelled data. By clustering similar images together, you can infer that images within the same cluster may share the same label or have similar properties. Then, using the known labels from your smaller labelled dataset, you can assign labels to entire clusters or refine the model's understanding of the data structure. This approach helps to enhance the classification process by effectively enlarging the training dataset and improving the model's accuracy and robustness.

# 2) Analysis

### Founder Requirements

**Founder 1: Software Engineering**

1. Scalability of the solution to support large numbers of auctions and user interactions.
2. Maintainability and understanding of the codebase for future modifications and extensions.
3. Preference for simple, efficient solutions that can integrate well with existing back-end systems.
4. Interest in adopting new technical areas and integrating new technologies, with a slight inclination towards open-source projects.

**Founder 2: Product Design and Technology**

1. Improvement of user experience in item categorization, potentially through top-10 accuracy for image classification.
2. Leveraging existing human moderators' work and data for enhancing the AI solution.
3. UI/UX integration that allows easy and efficient categorization from the user's perspective.
4. Addressing user feedback effectively and continuously improving the platform's user interface.

**Founder 3: Business and IT**

1. Cost-effective solution, mindful of the operational costs, particularly related to cloud services (IaaS).
2. Flexible and dynamic scalability in response to varying user demand.
3. Potential for distributing computational load, considering both back-end and front-end (user device) capabilities.
4. Ensuring robust and reliable service in alignment with the company's growth and external supply chain factors.

**Founder 4: Law and Human Resources**

1. Adherence to ethical AI development principles, particularly the FAST Track Principles: Fairness, Accountability, Sustainability, and Transparency.
2. Consideration of potential risks, biases, and limitations associated with AI deployment.
3. Ensuring a consistent and fair user experience across various markets, including emerging ones with less represented categories.
4. Establishing a long-term vision for AI adoption and continuous improvement in the company

### k-Nearest Neighbours (k-NN):

**All Requirements Met:** 3, 5, 7, 13, 14.

**Relevant Requirements Explained:**

* **Efficiency (Req. 3):** k-NN's simplicity and ease of implementation align with Founder 1's preference for efficient solutions that integrate well with existing systems.
* **User Experience (Req. 5):** Can improve user experience in item categorization, especially when the data is well-segmented into distinct classes.
* **UI/UX Compatibility (Req. 7):** The straightforward nature of k-NN supports a user-friendly interface for item categorization.
* **Ethical AI Principles (Req. 13):** k-NN's inherent simplicity aids in maintaining transparency in AI decision-making processes.
* **Bias Consideration (Req. 14):** The algorithm's performance depends heavily on the input data, requiring careful consideration to avoid biases.

**Requirements Potentially Not Fully Met:**

* **Scalability (Req. 1 & 10):** k-NN may struggle with scalability due to its reliance on distance computations for the entire dataset.
* **Complexity and Expertise (Req. 2):** Despite its simplicity, k-NN might require additional expertise in feature selection and distance metric optimization.
* **Resource Intensity (Req. 9 & 11):** Its computational intensity can increase with the size of the dataset, impacting cost and efficiency.

### Convolutional Neural Networks (CNNs) with Transfer Learning:

**All Requirements Met:** 1, 2, 3, 4, 5, 6, 7, 9, 10, 13, 14, 15, 16.

**Relevant Requirements Explained:**

* **Scalability (Req. 1):** Ideal for handling the company's growing data volume, enabling efficient processing of large image datasets.
* **User Experience (Req. 5):** Enhances user experience through accurate item categorization, crucial for the auction platform.
* **Cost-Effectiveness (Req. 9):** Transfer learning offers a balance between performance and resource utilization, contributing to long-term cost savings despite initial resource intensity.
* **Global Market Suitability (Req. 15):** Capable of classifying a diverse range of items, supporting varied categories prevalent in emerging markets.
* **Long-Term AI Vision (Req. 16):** Aligns with the company’s strategic vision for continuous AI development and improvement.

**Requirements Potentially Not Fully Met:**

* **Resource Intensity (Req. 9 & 11):** The resource demands of CNNs could pose challenges in terms of computational efficiency and associated costs.
* **External Supply Chain Factors (Req. 12):** Dependence on external datasets and pre-trained models may raise concerns regarding data availability and control.

### Integrated Feature Extraction:

**All Requirements Met:** 3, 5, 6, 7, 13, 14, 15, 16.

**Relevant Requirements Explained:**

* **Efficiency (Req. 3):** The integration of multiple feature extraction methods like edge detection, colour removal, and hand-crafted features enhances efficiency in processing and categorizing images.
* **User Experience (Req. 5 & 7):** By accurately capturing essential image features, this method improves user experience in item categorization and supports an intuitive UI/UX.
* **Data Utilization (Req. 6):** Effectively leverages existing datasets, including those reviewed by human moderators, for enhanced AI solution development.
* **Ethical AI Principles (Req. 13):** Integrated feature extraction can be designed to be transparent and fair, adhering to ethical AI development principles.
* **Bias Consideration (Req. 14):** The combination of different methods helps to address potential biases in the data, ensuring a more balanced and representative feature set.
* **Global Market Suitability (Req. 15):** Adaptable to a variety of item categories, beneficial for diverse and emerging markets.
* **Long-Term AI Vision (Req. 16):** Aligns with the long-term strategy for continuous AI development and improvement in image classification.

**Requirements Potentially Not Fully Met:**

* **Scalability (Req. 1 & 10):** The complexity of integrating multiple methods might pose challenges in scalability and real-time processing.
* **Complexity and Expertise (Req. 2):** Requires a nuanced understanding of different feature extraction methods and how they complement each other.
* **Resource Intensity (Req. 9 & 11):** The computational load might increase with the integration of multiple feature extraction techniques, impacting efficiency and costs.

### Support Vector Machines (SVMs):

**All Requirements Met:** 2, 5, 13, 14, 15, 16.

**Relevant Requirements Explained:**

* **Maintainability (Req. 2):** SVMs require expertise for parameter tuning and kernel choice, which might challenge maintainability without the necessary technical knowledge.
* **User Experience (Req. 5):** Effective in image classification, SVMs can enhance user experience through accurate item categorization.
* **Ethical AI Principles (Req. 13):** Properly implemented SVMs can contribute to ethical AI practices by ensuring fairness in classification outcomes.
* **Bias Consideration (Req. 14):** SVMs' dependency on kernel functions and parameter settings necessitates careful consideration to avoid biases in classification.
* **Global Market Suitability (Req. 15):** Effective for various types of image data, supporting the diverse product range in global markets.
* **Long-Term AI Vision (Req. 16):** Aligns with the vision of adopting robust and effective AI solutions for long-term usage.

**Requirements Potentially Not Fully Met:**

* **Scalability (Req. 1 & 10):** SVMs can become computationally intensive with large datasets, potentially impacting scalability.
* **Efficiency (Req. 3 & 9):** The resource intensity of training and tuning SVMs, especially with large image datasets, might conflict with efficiency and cost-effectiveness goals.
* **Complexity and Resource Intensity (Req. 11):** High computational demands of SVMs, especially for large-scale image classification, could be a concern in terms of resource allocation and processing efficiency.

### Random Forests:

**All Requirements Met:** 5, 7, 13, 14, 15, 16.

**Relevant Requirements Explained:**

* **User Experience (Req. 5 & 7):** The robustness and generalizability of Random Forests improve item categorization accuracy, enhancing the user experience and UI/UX.
* **Ethical AI Principles (Req. 13):** Random Forests, with their ensemble approach, contribute to fairness and transparency in classification, aligning with ethical AI practices.
* **Bias Consideration (Req. 14):** By aggregating multiple decision trees, Random Forests can mitigate individual biases, leading to more balanced classification outcomes.
* **Global Market Suitability (Req. 15):** Capable of handling diverse image data, Random Forests are adaptable to a variety of item categories, beneficial for global markets.
* **Long-Term AI Vision (Req. 16):** They align with the company's strategic vision for AI development, providing a robust and scalable solution for image classification.

**Requirements Potentially Not Fully Met:**

* **Scalability (Req. 1 & 10):** While individual trees are fast, a large ensemble can be computationally intensive, potentially affecting scalability with large datasets.
* **Efficiency (Req. 3 & 9):** The computational load of training and deploying numerous trees might challenge the efficiency and cost-effectiveness of the solution.
* **Complexity and Resource Intensity (Req. 11):** Managing a large number of decision trees can increase complexity and demand significant computational resources.

### Artificial Neural Networks (ANNs):

**All Requirements Met:** 4, 5, 6, 7, 13, 14, 15, 16.

**Relevant Requirements Explained:**

* **Technical Integration (Req. 4):** ANNs offer flexibility and adaptability in technical integration, suitable for diverse and complex classification tasks.
* **User Experience (Req. 5 & 7):** The capability of ANNs to learn complex patterns can significantly enhance the accuracy of item categorization, leading to an improved user experience and more intuitive UI/UX for the auction platform.
* **Data Utilization (Req. 6):** ANNs can effectively utilize both labelled and unlabelled data, leveraging the company's existing datasets for improved model training and feature extraction.
* **Ethical AI Principles (Req. 13):** With careful implementation, ANNs can adhere to ethical AI practices, ensuring fairness and transparency in classifications.
* **Bias Consideration (Req. 14):** The design and training of ANNs require attention to avoid ingraining biases, especially in the selection of training data and network architecture.
* **Global Market Suitability (Req. 15):** ANNs' ability to learn from diverse data types makes them suitable for classifying a wide range of items, supporting different market needs, including less represented categories.
* **Long-Term AI Vision (Req. 16):** Aligns with the company's vision for continuous AI improvement and adaptation, capable of evolving with changing market trends and data.

**Requirements Potentially Not Fully Met:**

* **Scalability and Resource Intensity (Req. 1, 9, 10 & 11):** Training large ANNs can be resource-intensive, posing challenges in terms of computational cost and scalability, especially with a growing dataset.
* **Complexity and Expertise (Req. 2):** The complexity of ANNs might require specialized AI expertise for effective implementation and ongoing maintenance, potentially impacting the company's ability to fully manage and understand the system.

### K-Means Clustering:

**All Requirements Met:** 3, 6, 13, 14.

**Relevant Requirements Explained:**

* **Efficiency (Req. 3):** K-Means is efficient for clustering large datasets, which can be beneficial as a preprocessing step in image classification, especially in organizing and simplifying image data.
* **Data Utilization (Req. 6):** Useful for organizing unlabelled data into meaningful clusters, K-Means can help make sense of the large volumes of images, facilitating more effective categorization and usage of the company's extensive image database.
* **Ethical AI Principles (Req. 13):** By nature, K-Means is a straightforward algorithm that contributes to transparency in data processing, aligning with ethical AI development principles.
* **Bias Consideration (Req. 14):** Careful implementation of K-Means can help avoid biases in data clustering, although the quality of outcomes heavily relies on the choice of features and number of clusters.

**Requirements Potentially Not Fully Met:**

* **Scalability and Dynamic Adaptability (Req. 1 & 10):** While K-Means is efficient with smaller datasets, scalability may be a concern with very large collections of images, impacting its effectiveness as the company grows.
* **Complexity and Expertise (Req. 2):** Determining the optimal number of clusters and feature selection requires expertise, which could challenge the maintainability and adaptability of the system.
* **Global Market Suitability (Req. 15):** K-Means might struggle with categorizing items correctly in markets where the item characteristics significantly differ from the majority data, leading to less accuracy in less represented categories.
* **Long-Term Adaptability (Req. 16):** The static nature of K-Means clustering may not align with the company's vision for dynamic and evolving AI solutions, especially in rapidly changing market environments.

### Autoencoders:

**All Requirements Met:** 3, 6, 13, 14, 15.

**Relevant Requirements Explained:**

* **Efficiency (Req. 3):** Autoencoders are efficient for learning compressed representations of images, aiding in data simplification and feature extraction.
* **Data Utilization (Req. 6):** Particularly valuable for working with the company's large amount of unlabelled image data, enabling effective feature extraction without extensive labelling.
* **Ethical AI Principles (Req. 13):** By focusing on feature extraction from data, autoencoders can contribute to ethical AI practices, particularly in the context of unbiased data representation and processing.
* **Bias Consideration (Req. 14):** The nature of autoencoders in learning data representations can help in identifying and mitigating biases, especially when trained on diverse datasets.
* **Global Market Suitability (Req. 15):** Autoencoders can adapt to various types of image data, making them suitable for handling diverse item categories across different markets.

**Requirements Potentially Not Fully Met:**

* **Scalability and Resource Intensity (Req. 1, 9, 10 & 11):** Training deep autoencoders can be resource-intensive, posing challenges in scalability, especially with large image datasets.
* **Complexity and Expertise (Req. 2):** Implementing and fine-tuning autoencoders require a certain level of technical expertise in neural networks, which might impact the maintainability and adaptability of the system within the company.

### Principal Component Analysis (PCA):

**All Requirements Met:** 3, 6, 9, 10, 13, 14.

**Relevant Requirements Explained:**

* **Efficiency (Req. 3):** PCA efficiently reduces the dimensionality of image data, simplifying the classification process and reducing computational load.
* **Data Utilization (Req. 6):** Effective for preprocessing, PCA can enhance the utility of existing datasets by focusing on the most informative features.
* **Cost-Effectiveness (Req. 9):** By reducing data complexity, PCA contributes to a more cost-effective solution, minimizing the need for extensive computational resources.
* **Dynamic Scalability (Req. 10):** PCA's ability to reduce feature space complexity aids in scalability, adapting to increasing data volumes.
* **Ethical AI Principles (Req. 13):** PCA's transparent and systematic approach to feature reduction aligns with ethical AI practices by ensuring data processing fairness.
* **Bias Consideration (Req. 14):** By focusing on principal components, PCA can help in identifying underlying structures in the data, potentially revealing, and mitigating biases.

**Requirements Potentially Not Fully Met:**

* **Complexity and Expertise (Req. 2):** Determining the optimal number of components and interpreting PCA results can require statistical expertise, impacting ease of use and integration.
* **Global Market Suitability (Req. 15):** PCA's linear nature might not capture all the nuances in diverse data types, especially in global markets with less represented categories.

### K-Means Clustering with Labelled Images:

**All Requirements Met:** 3, 5, 6, 7, 13, 14, 15.

**Relevant Requirements Explained:**

* **Efficiency (Req. 3):** This method efficiently categorizes large amounts of unlabelled data using a smaller set of labelled examples, optimizing the process of image classification.
* **User Experience (Req. 5 & 7):** By improving the accuracy of categorization, it enhances the user experience and the efficiency of the user interface.
* **Data Utilization (Req. 6):** Effectively leverages the mix of labelled and unlabelled data, especially useful given the company's existing datasets.
* **Ethical AI Principles (Req. 13):** The semi-supervised nature of this approach, guided by labelled data, can ensure more fairness in categorization.
* **Bias Consideration (Req. 14):** With careful label selection, it can help reduce biases in the classification process.
* **Global Market Suitability (Req. 15):** Useful for diverse product categories, enhancing the accuracy of classification across different markets.

**Requirements Potentially Not Fully Met:**

* **Scalability (Req. 1 & 10):** While efficient with smaller datasets, scalability might be a concern when clustering very large collections of images.
* **Complexity and Expertise (Req. 2):** Determining the optimal number of clusters and integrating labelled and unlabelled data can require specific expertise in data science and clustering techniques.

# 3) Recommendation [~500 words]

“[…] *drawing on (2) to present a conclusion that argues for a single overall approach to the problem that you believe the company should pursue, and giving your reasons why. No single solution is perfect and this will involve acknowledging weaknesses as well as highlighting strengths.*”

\*\*Create a table of techniques/components against requirements.\*\*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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|  | **Founder 1** | | | | **Founder 2** | | | | **Founder 3** | | | | **Founder 4** | | | |
| **Requirements** | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* | *13* | *14* | *15* | *16* |
| ***k-Nearest Neighbours (k-NN)*** | Close with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill |
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| ***K-Means Clustering*** | Close with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill |
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| ***Principal Component Analysis (PCA)*** | Close with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill |
| ***K-Means Clustering with Labelled Images*** | Close with solid fill | Close with solid fill | Checkmark with solid fill | Close with solid fill | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill |

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*Notes*

\*\*Pick the correct combination that covers the most requirements and is the most feasible

\*\*Most **Reqs** can be covered by most combination, e.g., **Artificial Neural Networks (ANNs) with Principal Component Analysis (PCA)**, k-Nearest Neighbours (k-NN) with Integrated Feature Extraction, Support Vector Machines (SVMs) with Autoencoders, **Random Forests with PCA**

\*\*But the main trade-off is between **Effectiveness** vs **Scalability**

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# Reference list

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